

# Developments Toward a New Cloud Analysis and Prediction System

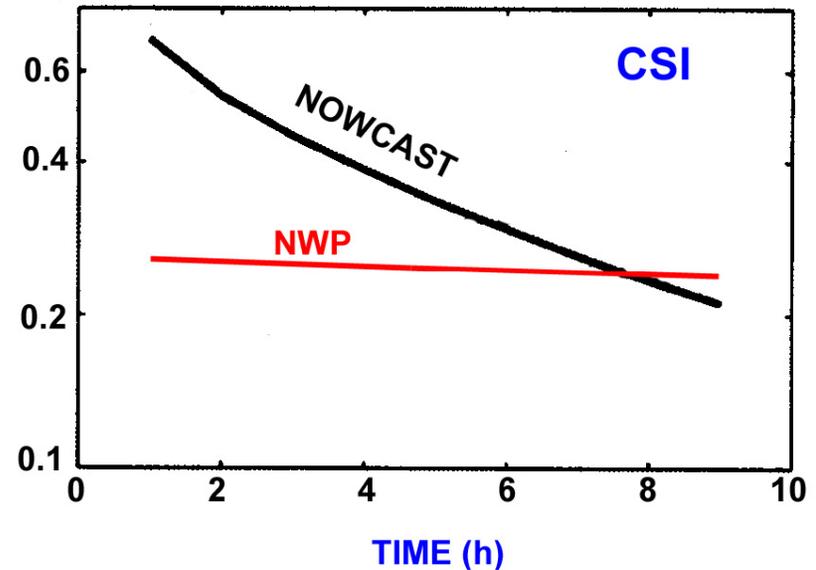
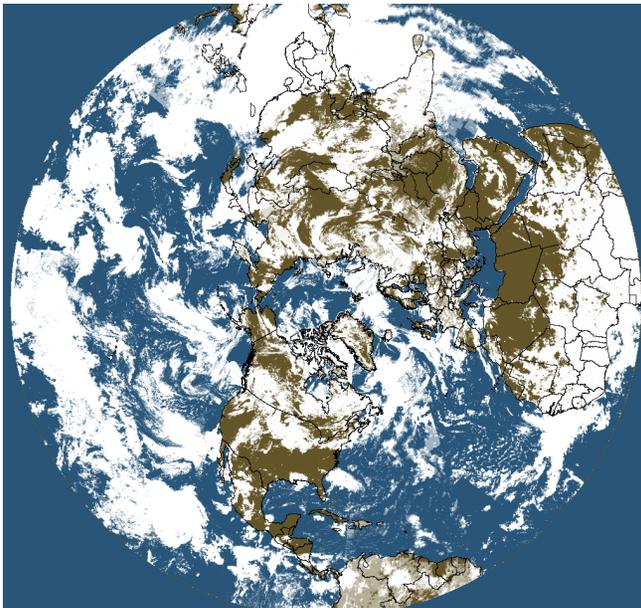
Tom Auligné

Mike Duda, Aimé Fournier, Hans Huang, Hui-Chuan  
Lin, Zhiquan Liu, Arthur Mizzi, Thomas Nehrkorn,  
Syed Rizvi, Craig Schwartz, Xin Zhang

*LAPS Users' Workshop - Boulder, Colorado– Oct, 25-27 2010*

# The AFWA Coupled Analysis and Prediction System (ACAPS) project

World-  
Wide  
Merged  
Cloud  
Analysis



0.1 mm hourly precipitation skill scores over 21 days  
From Lin et al. (2005), courtesy Jenny Sun

*GOAL: Develop an analysis and prediction system of 3D cloud properties combined with the dynamical variables.*

# Outline

- Cloud-affected Satellite Radiances
- Representativeness Error
- Inhomogeneous, flow dependent background errors
- Displacement Analysis

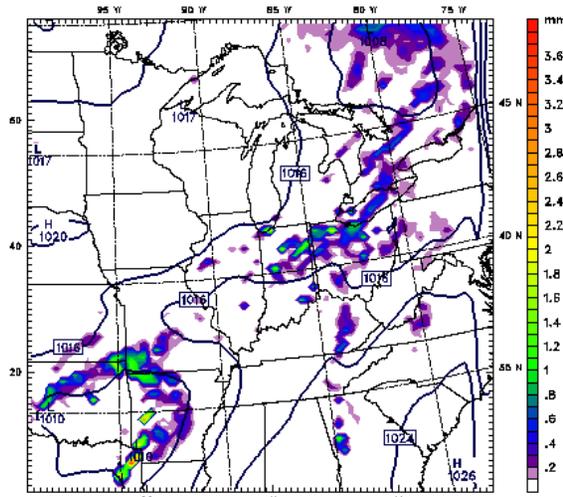
# Cloud-affected Satellite Radiances

# Assimilation of simulated cloud-affected radiances in WRF 3DVar

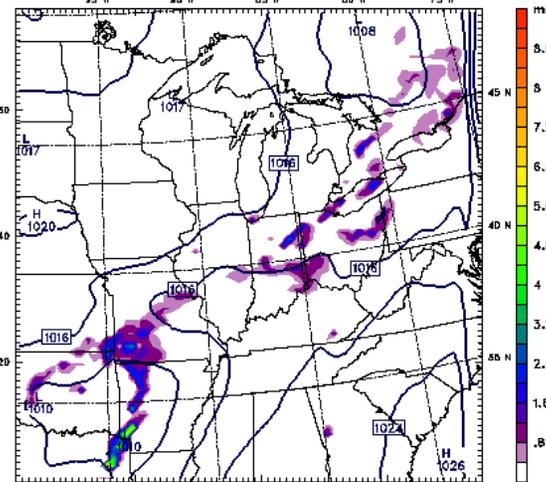
- Use total water  $Q_t = Q_{wv} + Q_{clw} + Q_{rain}$  instead of individual hydrometeors as a control variable
- *Use a warm-rain microphysics scheme's TL&AD for partitioning  $Q_t$  increment into  $Q_{wv}$ ,  $Q_{clw}$  &  $Q_{rain}$ . (Xiao et al., 2007)*
- CRTM as cloudy radiance observation operator
- *Minimization starts from a **cloud-free background**, this scenario can be realistic for less accurate cloud/precip. forecast in the real world*
- Perfect background for other variables (T,Q etc.)
- *Perfect observations (no noise added to the simulated Tbs)*
- 2 outer-loops

# Simulated SSMI/S radiances: 3DVar

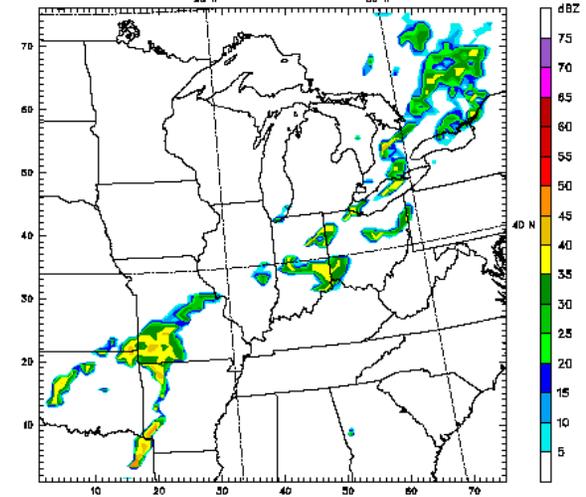
Column-Integrated cloud water



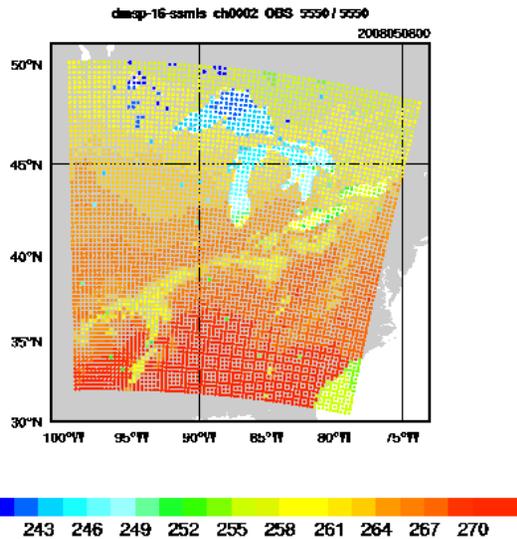
Column-Integrated rain water



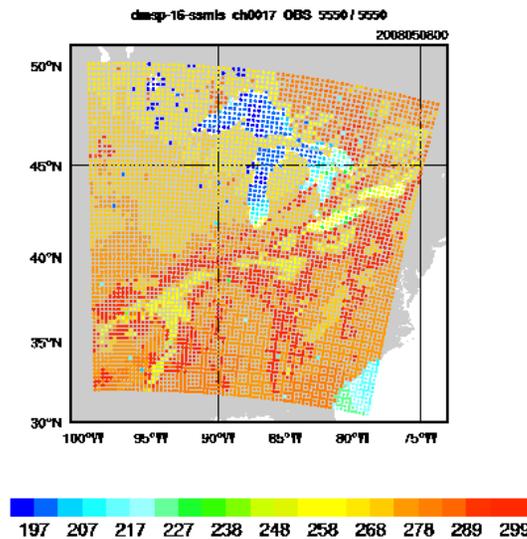
Radar Reflectivity



Simulated Ch2 Tbs



Simulated Ch17 Tbs

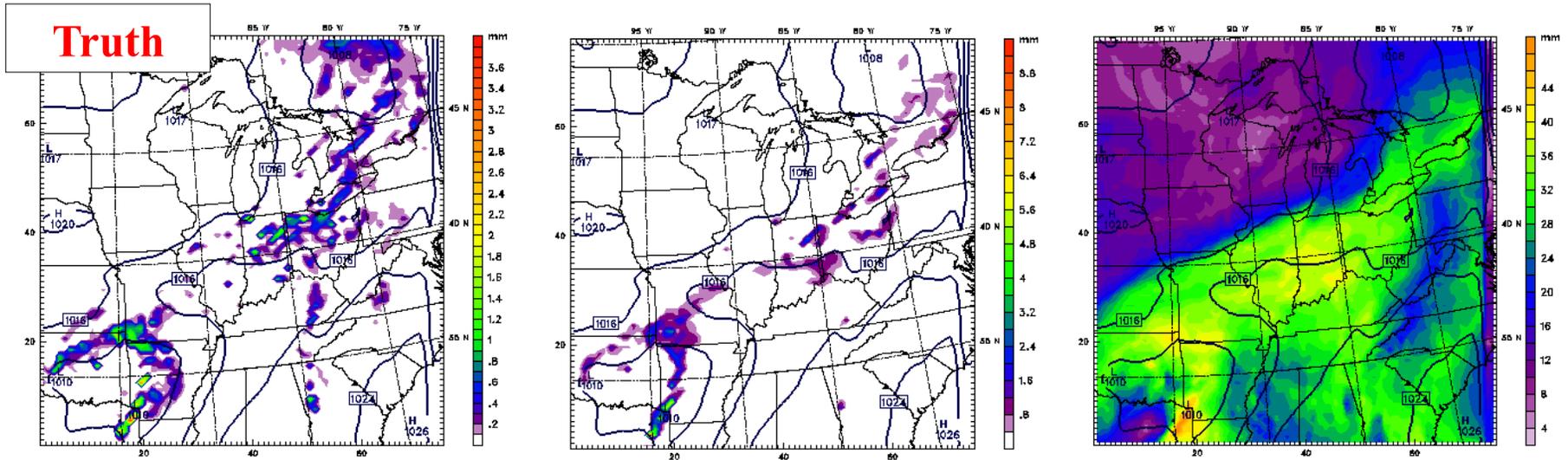


Model = “truth” for SSMI/S radiance simulation

Only liquid hydrometeors considered

SSMIS radiances (ch 1~6, 8~18) simulated at each grid-point using CRTM

# Simulated SSMI/S radiances: 3DVar

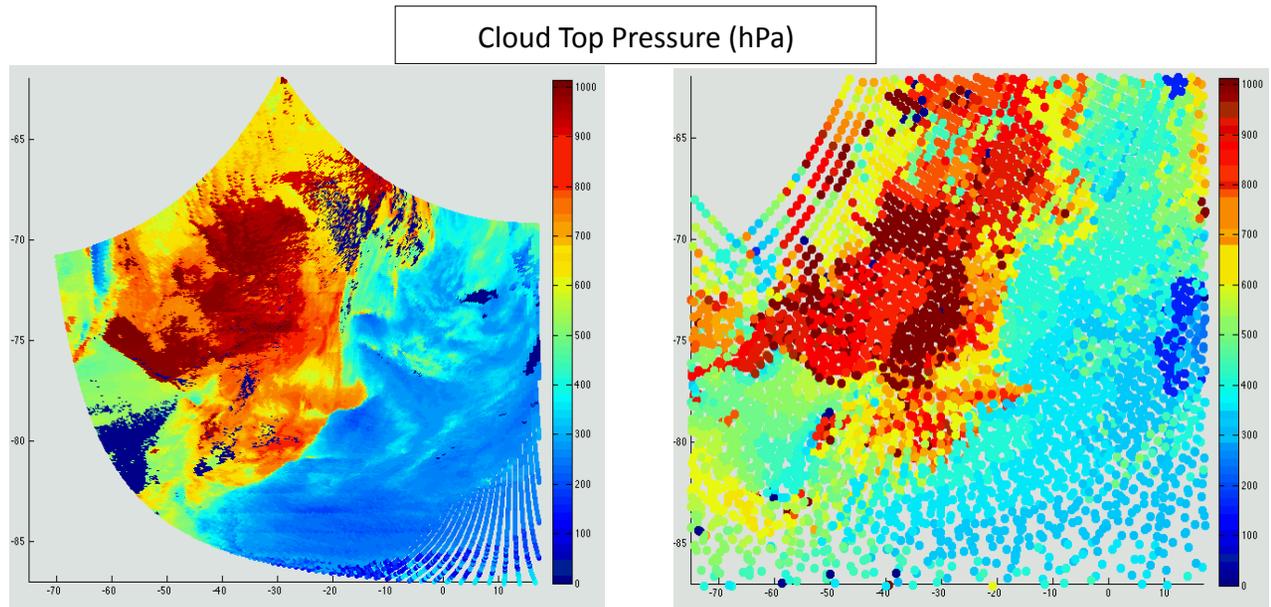
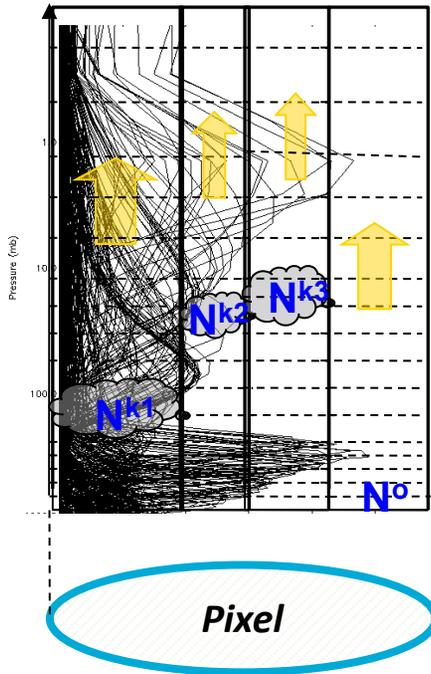


# Cloud Detection for IR sounders

$$R_v^{Cld} = N^{\circ} R_v^{\circ} + \sum_{k=1}^n N^k R_v^{\bullet k}$$

Cloud fractions  $N^k$  are adjusted *variationally* to fit observations:

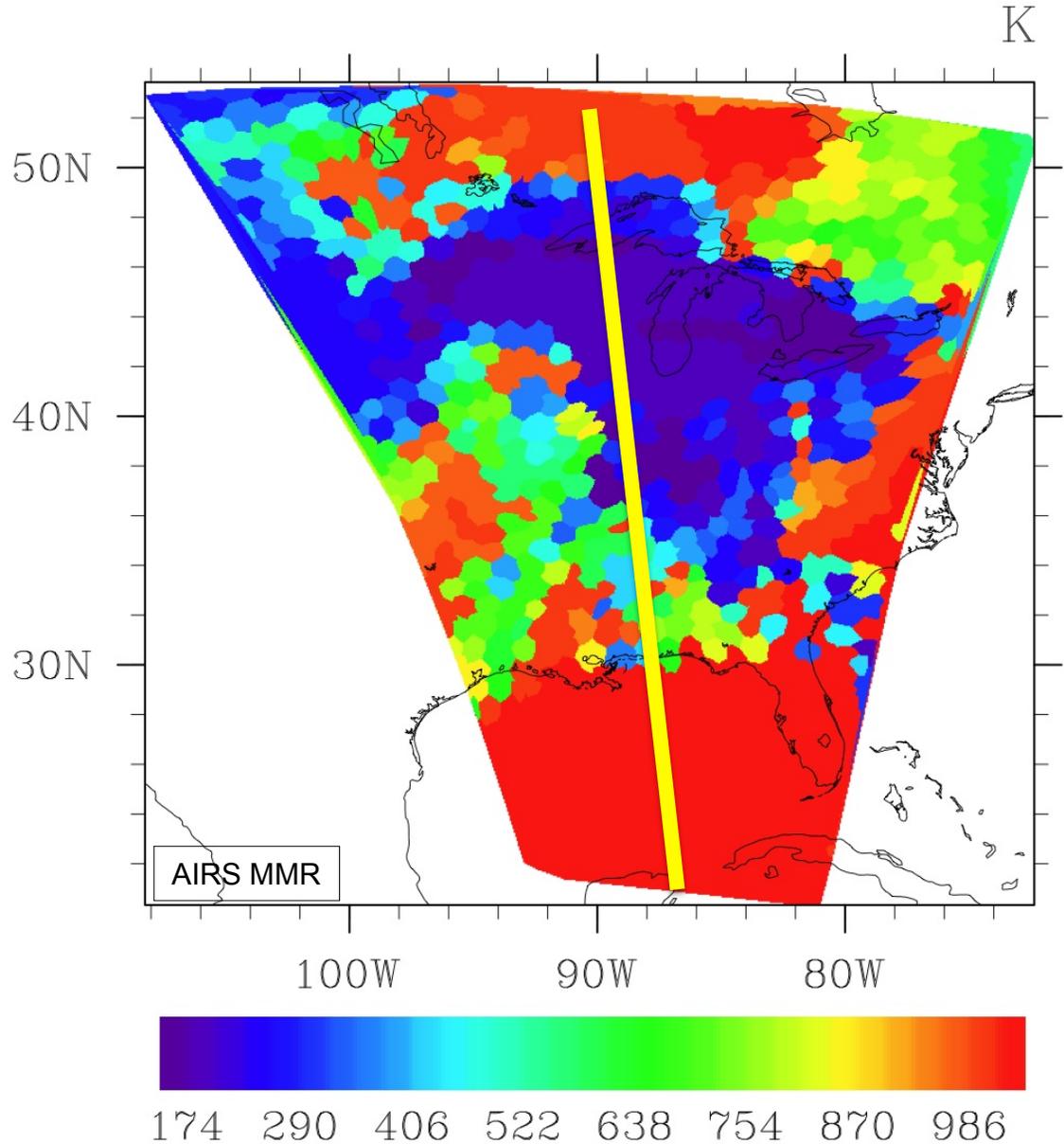
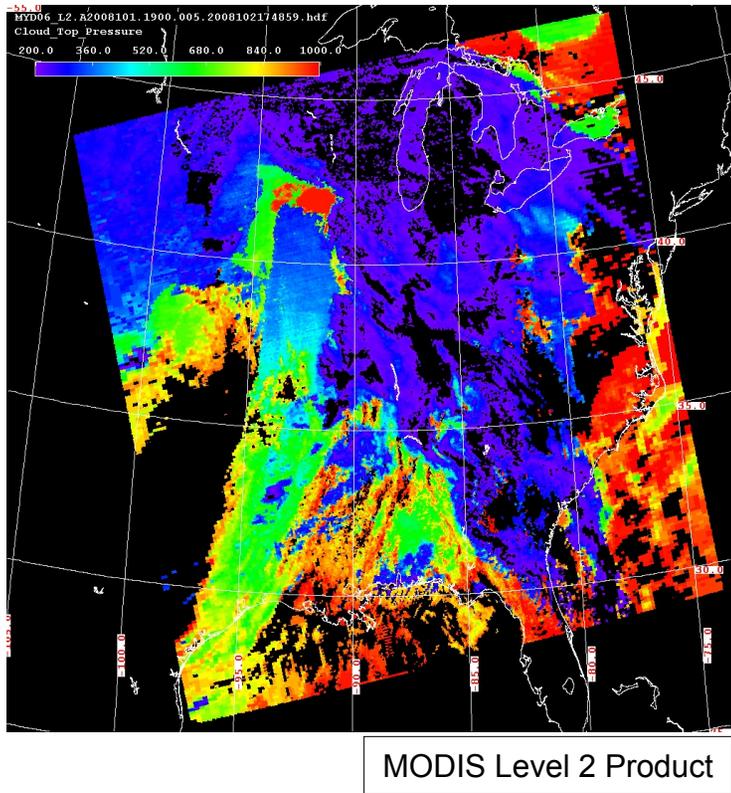
$$J(N) = \frac{1}{2} \sum_v \left( \frac{R_v^{Cld} - R_v^{Obs}}{R_v^{\circ}} \right)^2 \quad \text{with} \quad \begin{cases} 0 \leq N^k \leq 1, \forall k \in [0, n] \\ N^{\circ} + \sum_{k=1}^n N^k = 1 \end{cases}$$



MODIS Level2

AIRS MMR

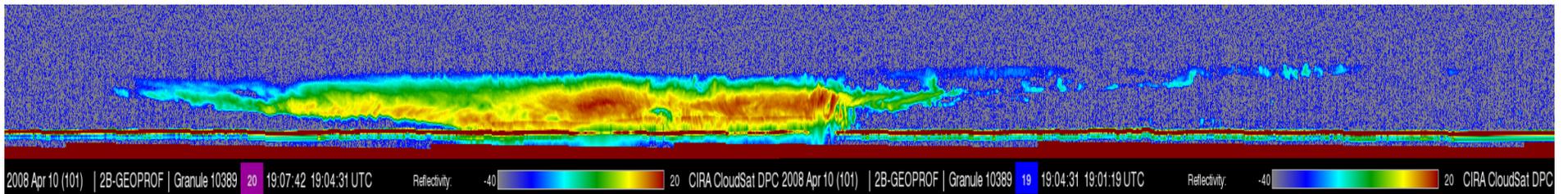
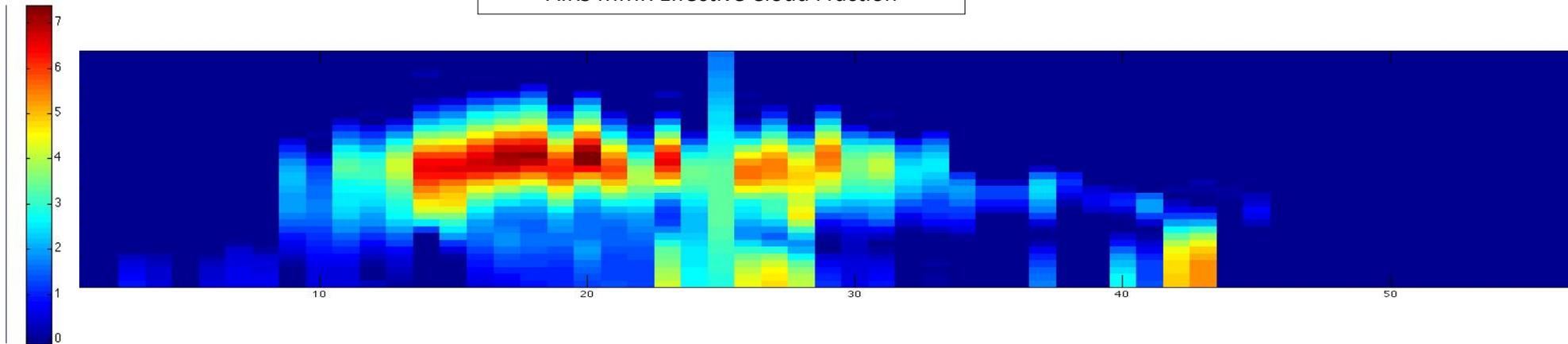
# Cloud Detection for IR sounders



GSI result

# Cloud Detection for IR sounders

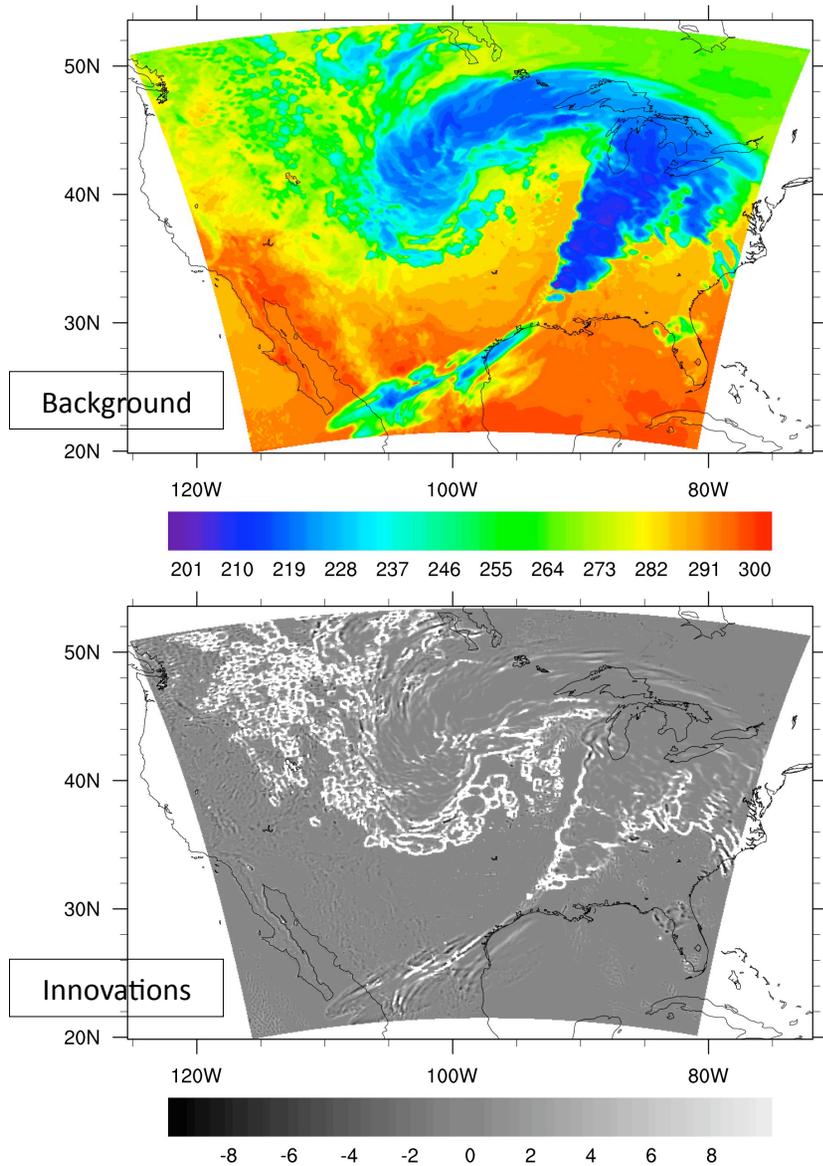
AIRS MMR Effective Cloud Fraction



CloudSat Reflectivity

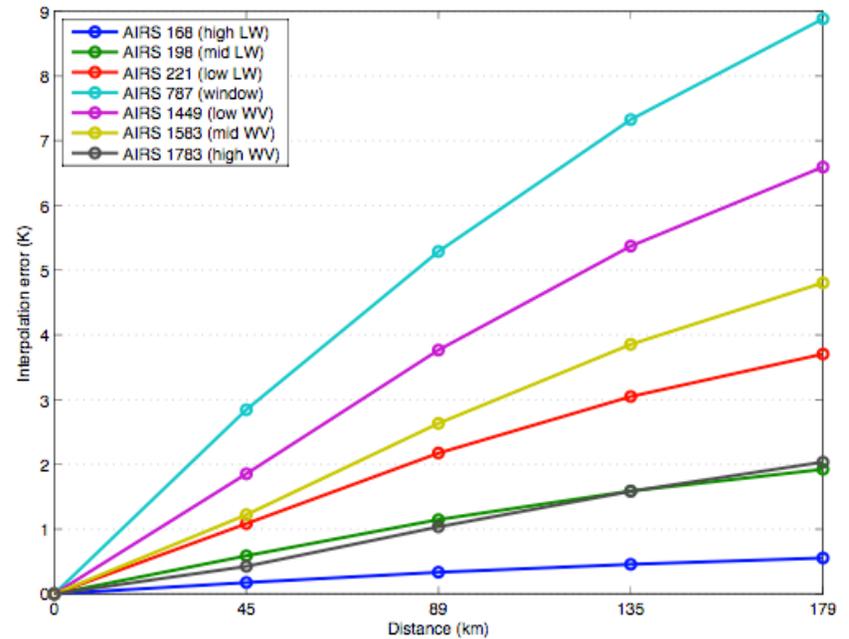
# Representativeness Error

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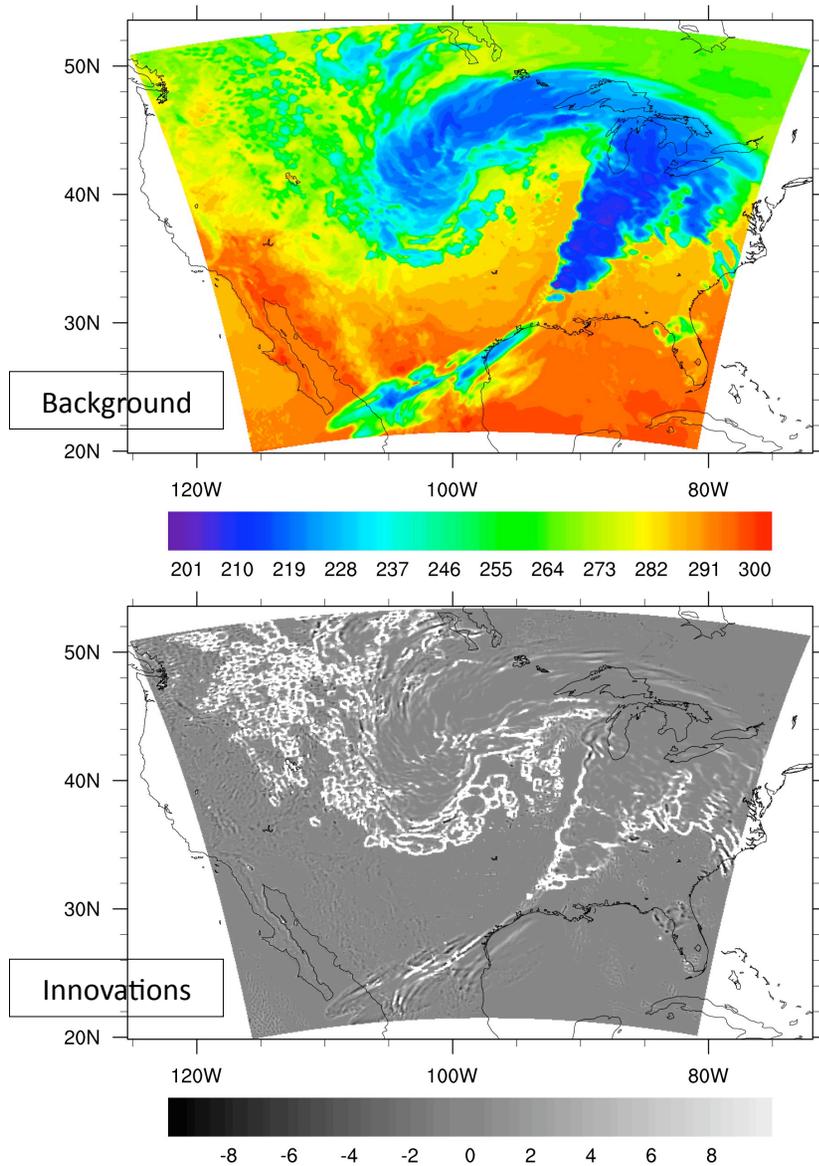


Simulated mismatch in resolution:

- Perfect observations (high resolution)
- Perfect Background (lower resolution)

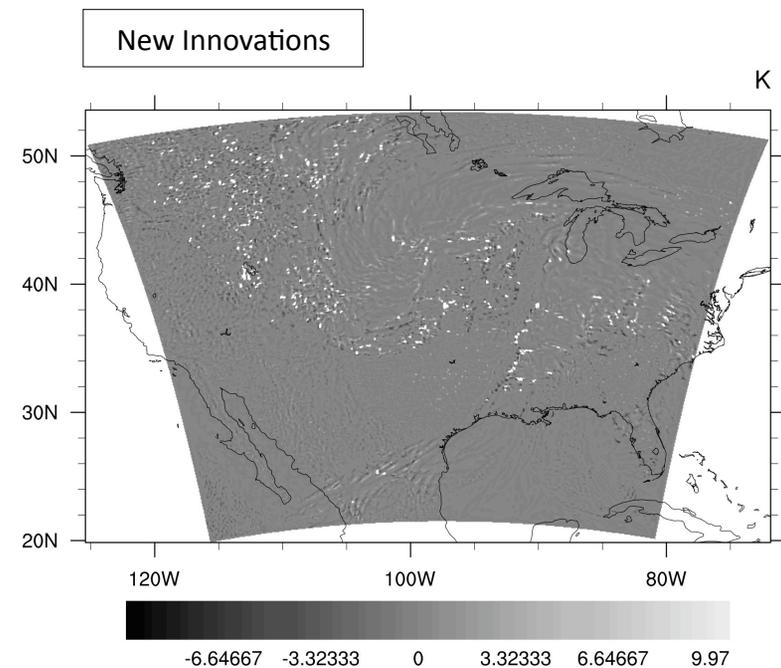


# Representativeness Error

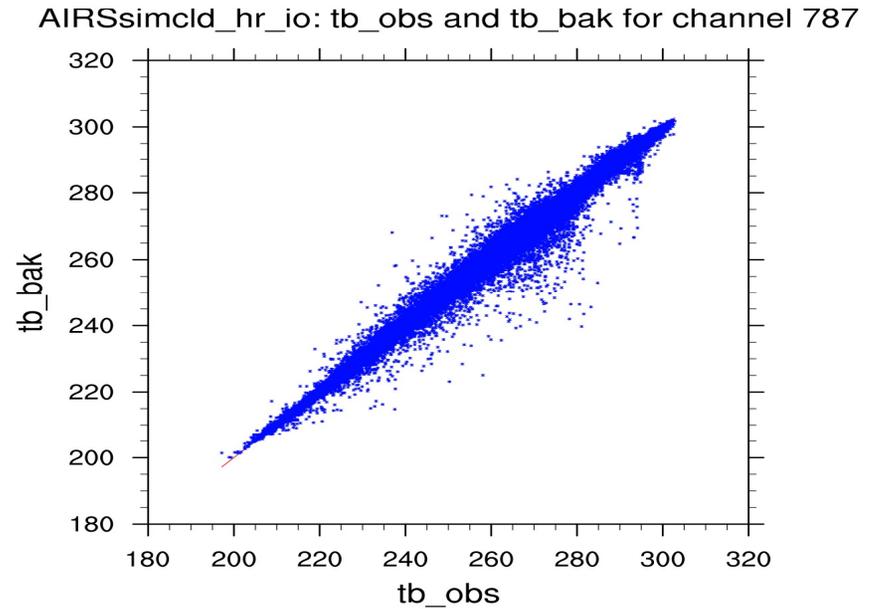
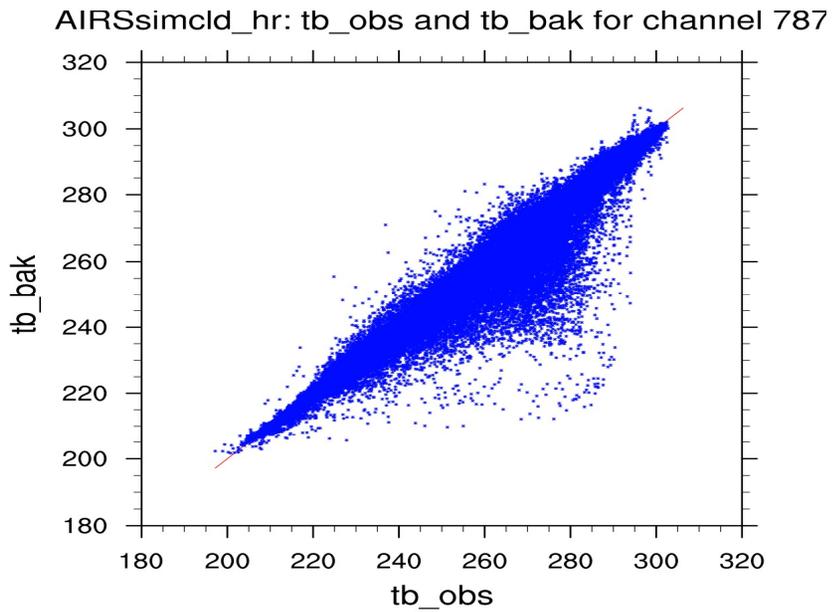


New interpolation scheme:

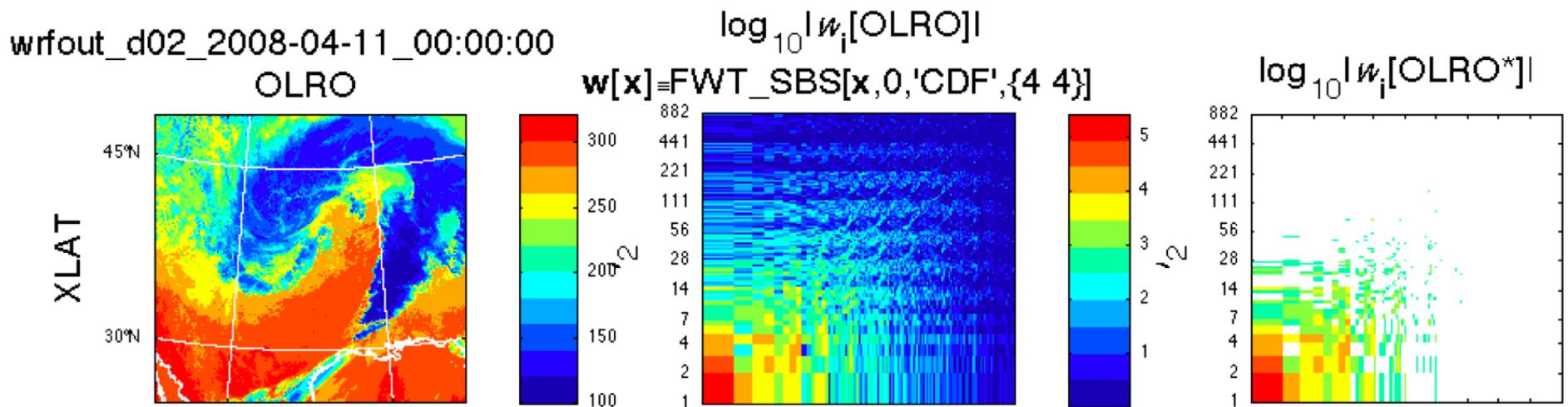
1. Automatic detection of sharp gradients
2. New “proximity” for interpolation



# Representativeness Error

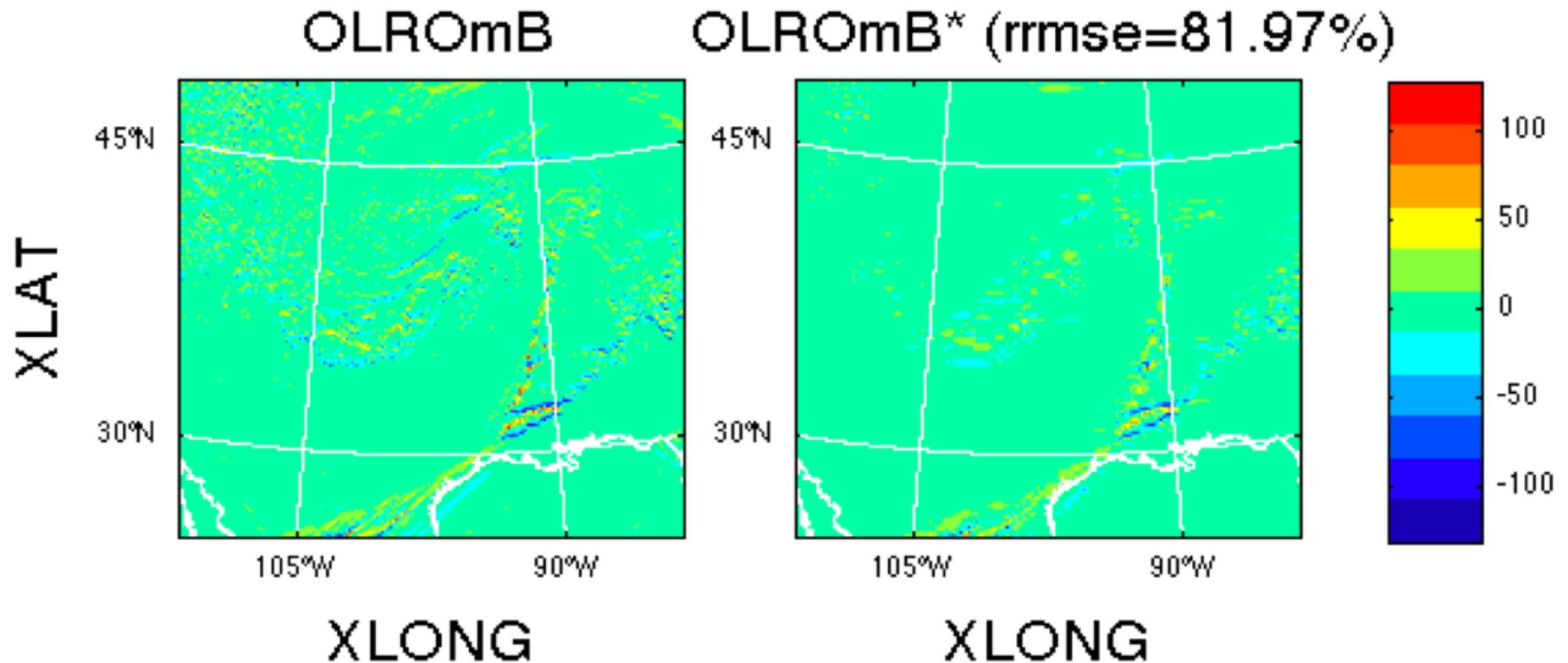


# Isolate innovations scale-by-scale while preserving physical-space localization



By sorting and comparing  $|w_i|$  (*center*) for obs.  $y_o$  (*left*) & background  $y_b$  we can isolate a multi-scale subset  $i \in \mathbb{I}$  (*right*) from which *equivalent* representations  $y_o^*$  and  $y_b^*$  of  $y_o$  and  $y_b$  can be reconstructed...

## Reduction in representativeness error

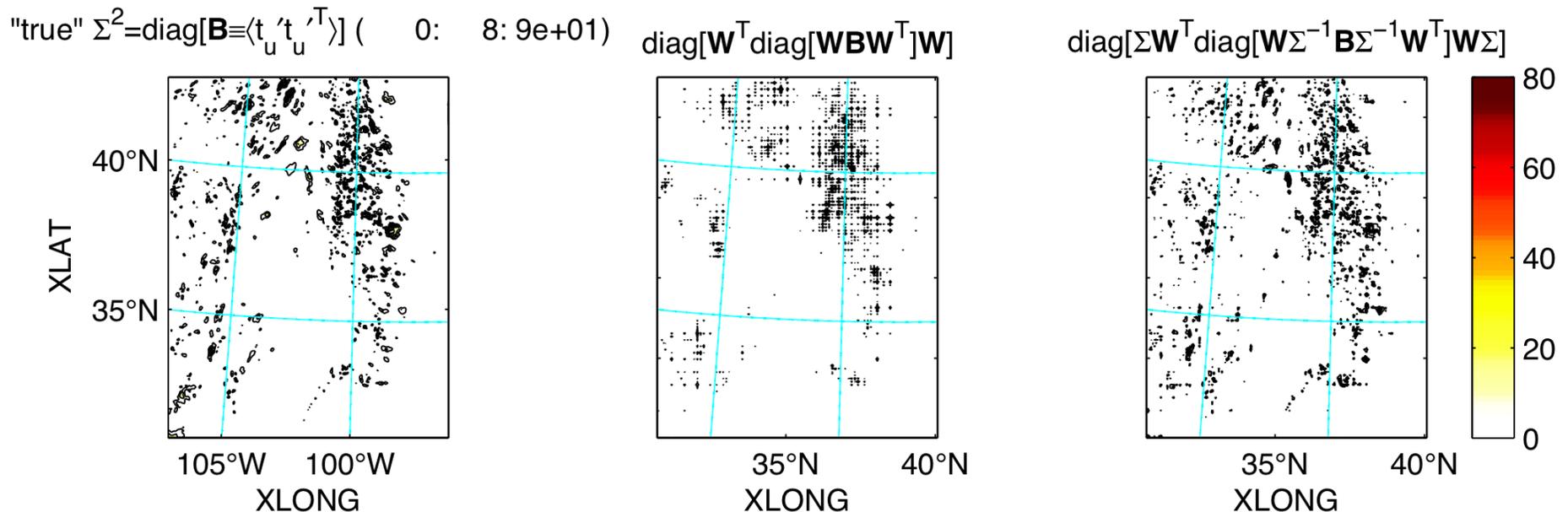


The raw  $y_o - y_b$  (left) includes errors due to  $y_o$  and  $y_b$  coming from completely different representations, that (hypothetically) have been *reconciled* by the foregoing wavelet-coefficient selection procedure.

Inhomogeneous, flow-dependent  
background error covariances

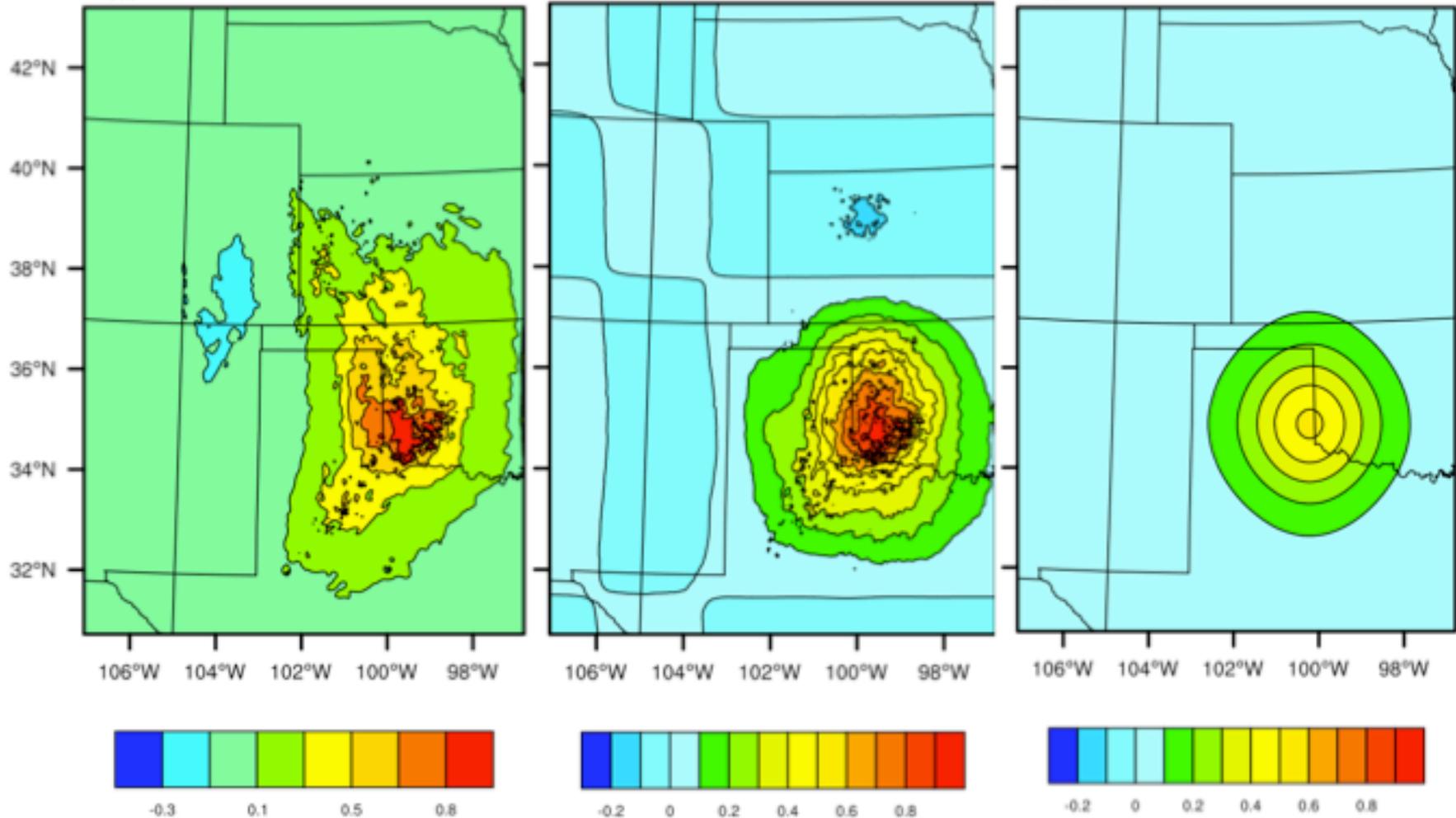
# Wavelet representation of Background Error Covariance Matrix

Background covariance can be *efficiently* modeled by assuming diagonality of the wavelet-coefficient covariance matrix (FISHER & ANDERSSON, DECKMYN & BERRE).



- The normalization with  $\Sigma^2 = \text{diag} \mathbf{B}$  (left) yields a model with *fewer* artifacts (right) than does  $\Sigma = \mathbf{I}$  (center) (as found by D&B earlier).
- In these plots  $\mathbf{x}$  is unbalanced temperature anomaly in a 30-member ensemble computed by DOWELL with horizontal resolution  $N = 450 \times 350$ .

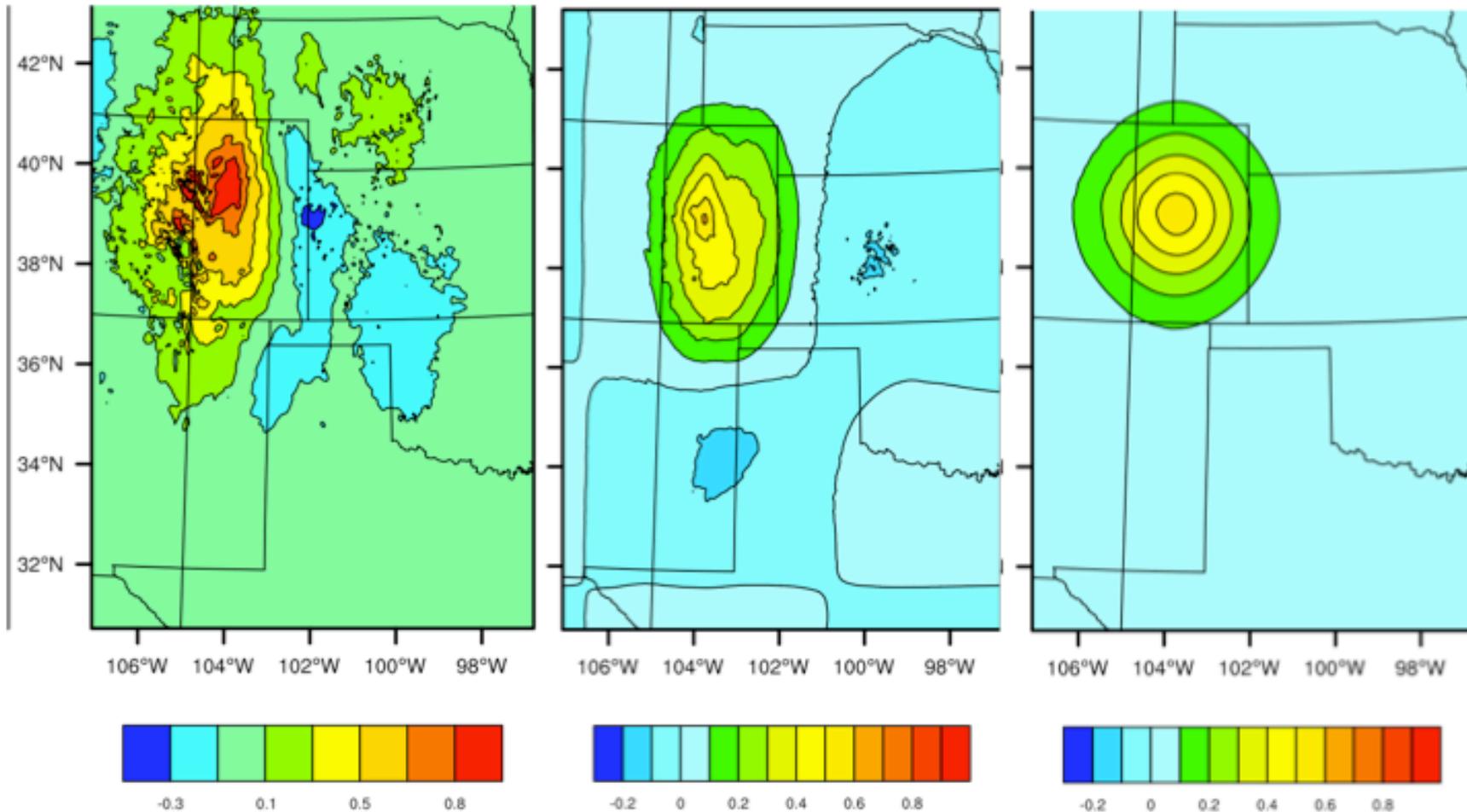
New **B** (center, 7C30 wavelet) represents heterogeneity (left, ensemble), unlike homogeneous recursive filters (right).



from an  $E = 30$ -member  $N = 351 \times 451$ , 5-level dataset.

- Note that the wavelets represent some multi-scale anisotropic features such as the SW-NE structures over N Texas.

Wavelet **B** model (center) captures anisotropy (left), unlike recursive filters (right).

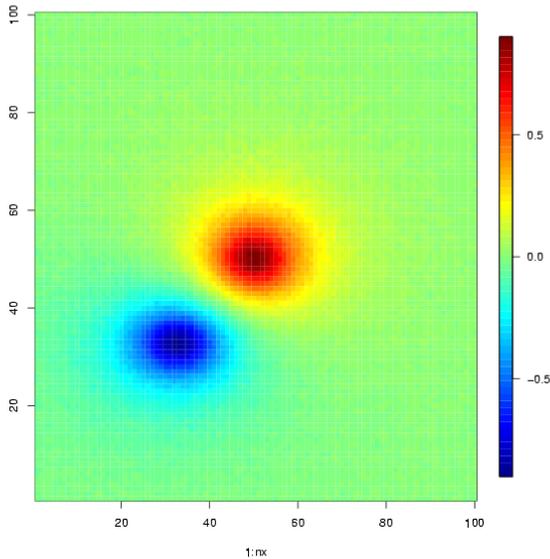


- Response to an observation at  $\lambda = -104^\circ$ ,  $\phi = 39^\circ$ ,  $\eta = 0.28$ .
- The *overall* horizontal scale is an adjustable parameter  $\text{len\_scaling} = 0.9$  (for RF),  $\text{nb} = 7$  (for wavelets) and  $\text{alpha\_corr\_scale} = 200\text{km}$  (for ensemble), each of which has only been roughly calibrated.

# Displacement Analysis

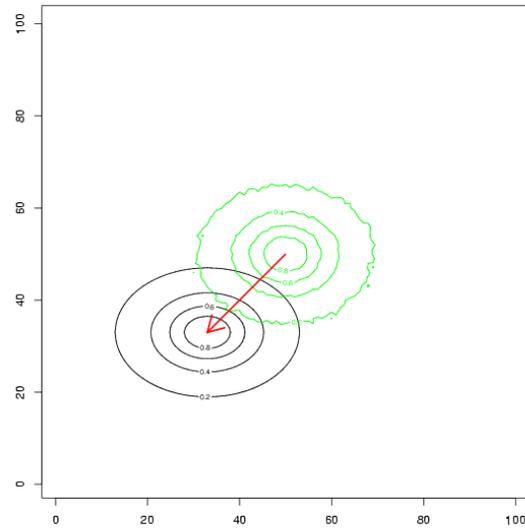
# Displacement, Field Alignment, Morphing Analysis, ...

background error



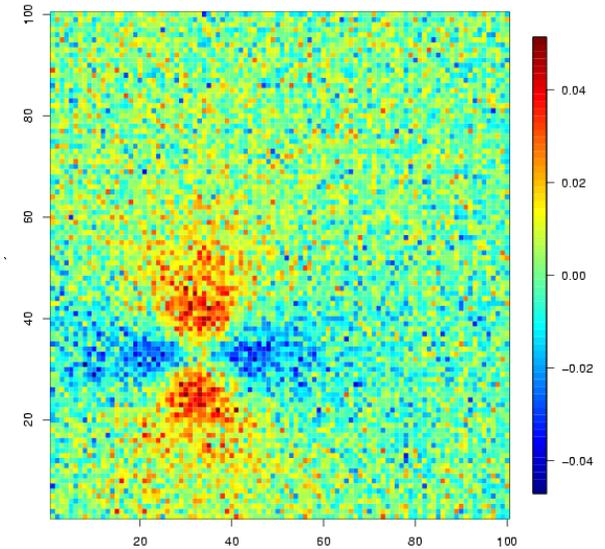
=>

displacements of coherent features



+

additive (residual) error



# Displacement Analysis Prototype

- based on feature calibration and alignment implementation by Grassotti et al. (1999)
- derive displacement vectors by minimizing an objective function:

$$J = J_{res}(y^{obs}, y^{bg}, \delta x, \delta y) + J_{pen}(\delta x, \delta y)$$

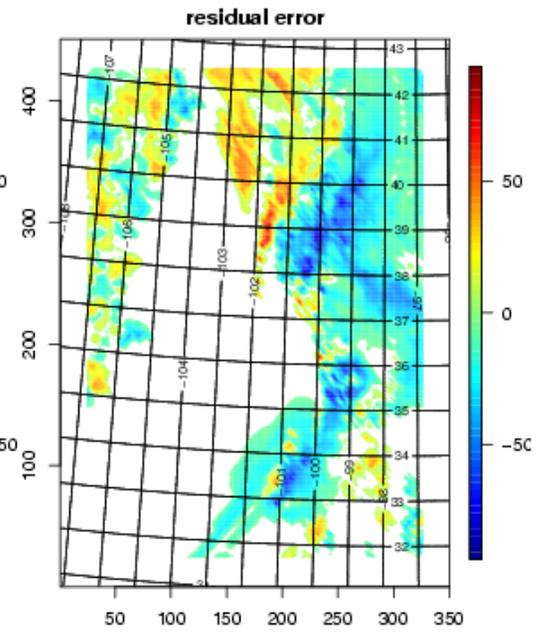
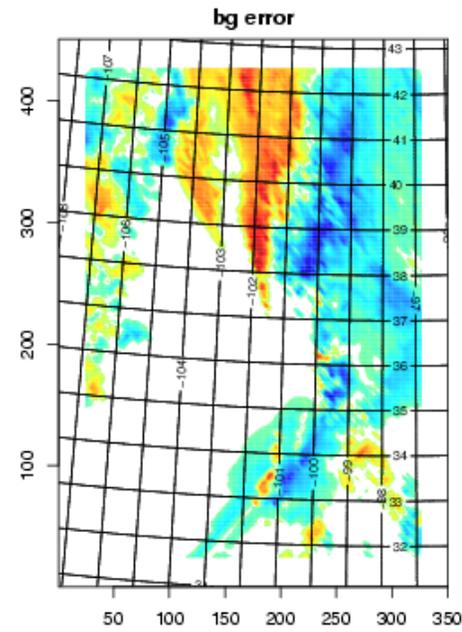
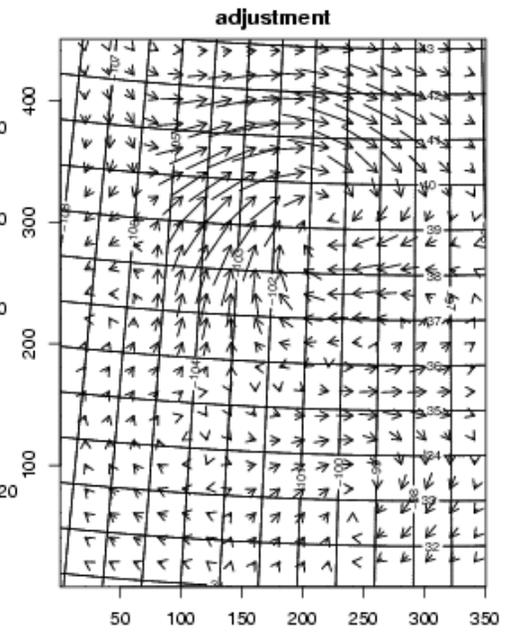
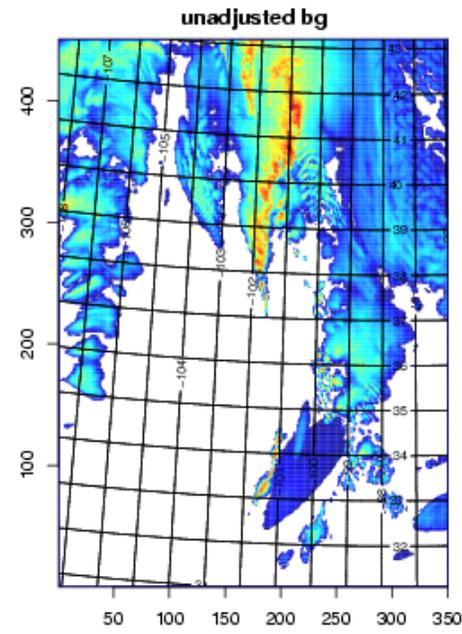
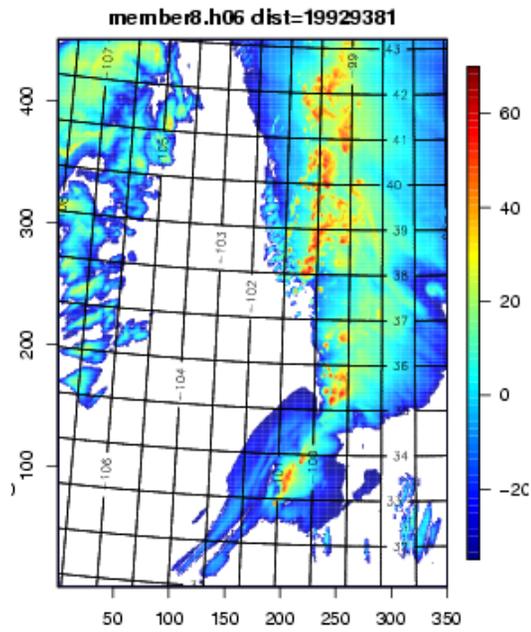
- residual errors after adjustment of the background:

$$J_{res} = \sum w_{obs} (y^{obs}(x, y) - y^{bg}(x + \delta x, y + \delta y))^2$$

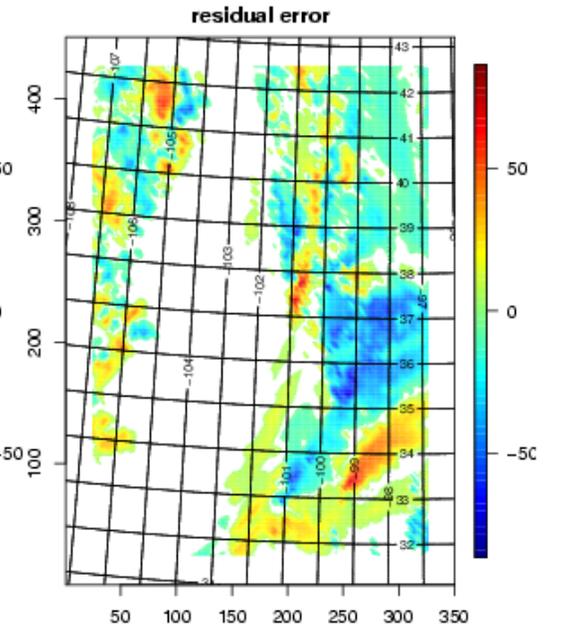
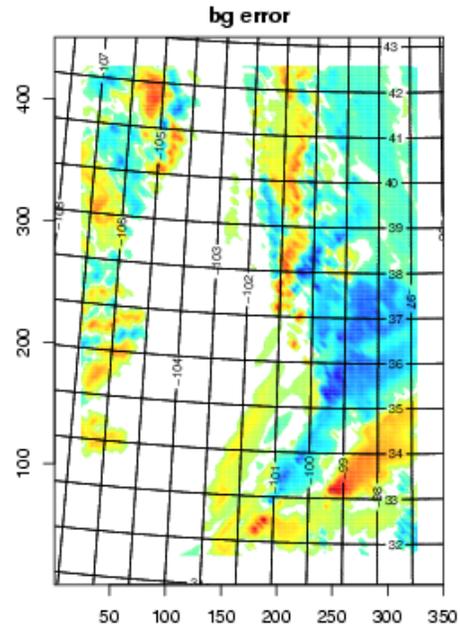
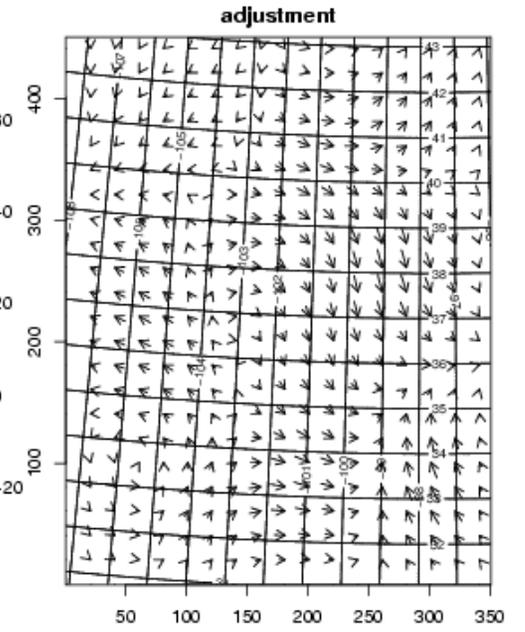
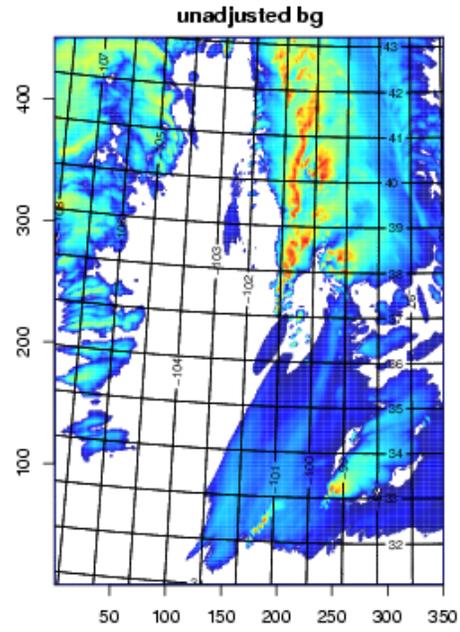
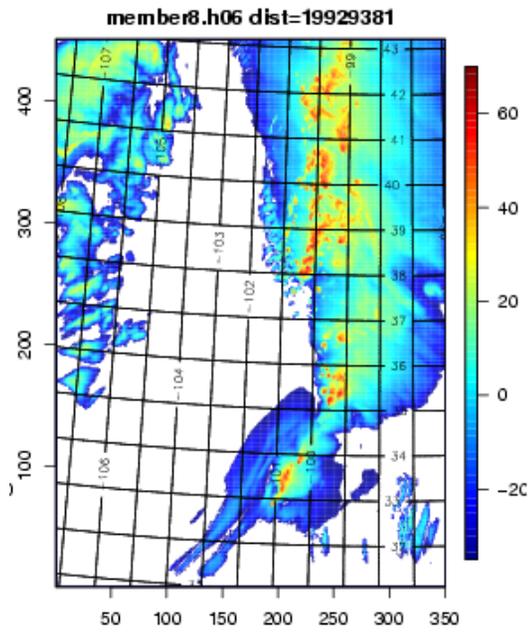
# Displacement DA Prototype

- **penalty function  $J_{pen}$  constrains**
  - maximum size of displacements (“barrier”)
  - mean square size of displacements
  - noisiness of displacement field (Laplacian)
  - divergence of displacement field
- **Implementation details**
  - use truncated spectral representation of displacements
  - use nonlinear optimization software
  - use adjoint to compute gradient of J

member11.h06.dbzmax.23.9.sxy45.sobs15.n5.gpadivb



member1.h06.dbzmax.23.9.sxy45.sobs15.n5.gpadivb



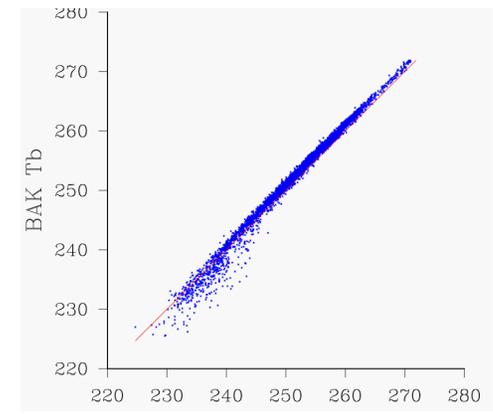
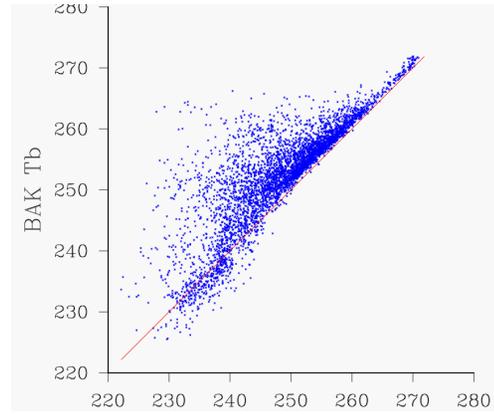
# Conclusion

- Start with regional prototype, based on WRF
- Evolve to global system, based on MPAS
- Major data assimilation challenges associated with clouds
  - non-linearities, non-Gaussianity,
  - under-observed phenomena,
  - model error, ...

Thank you for your attention...

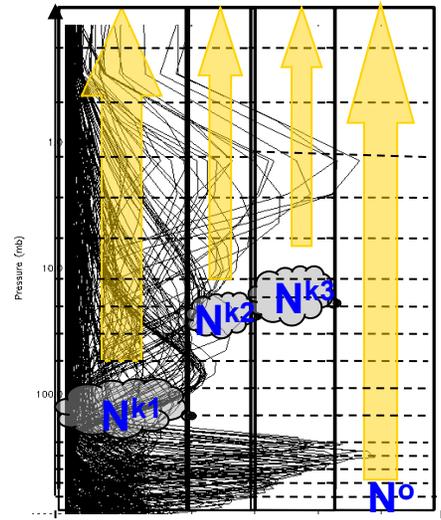
# Cloudy IR Radiances

## New Linear Observation Operator

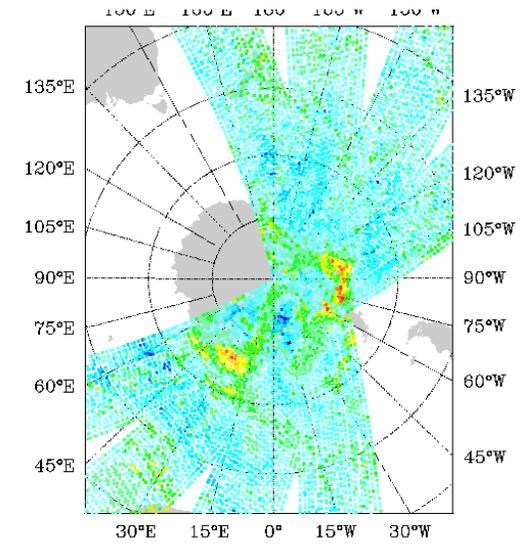
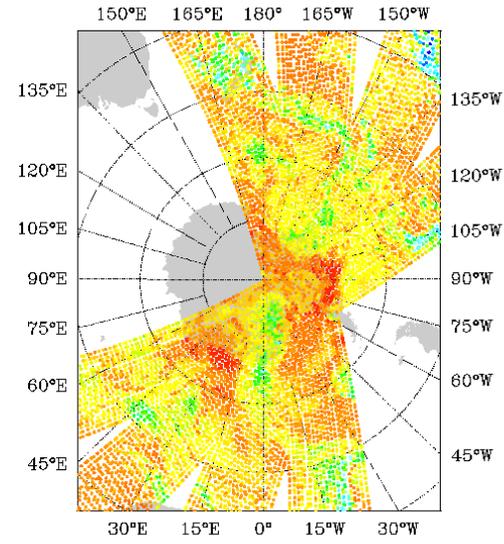


$$R_v^{Obs} - R_v^o$$

$$R_v^{Obs} - R_v^{Cld}$$

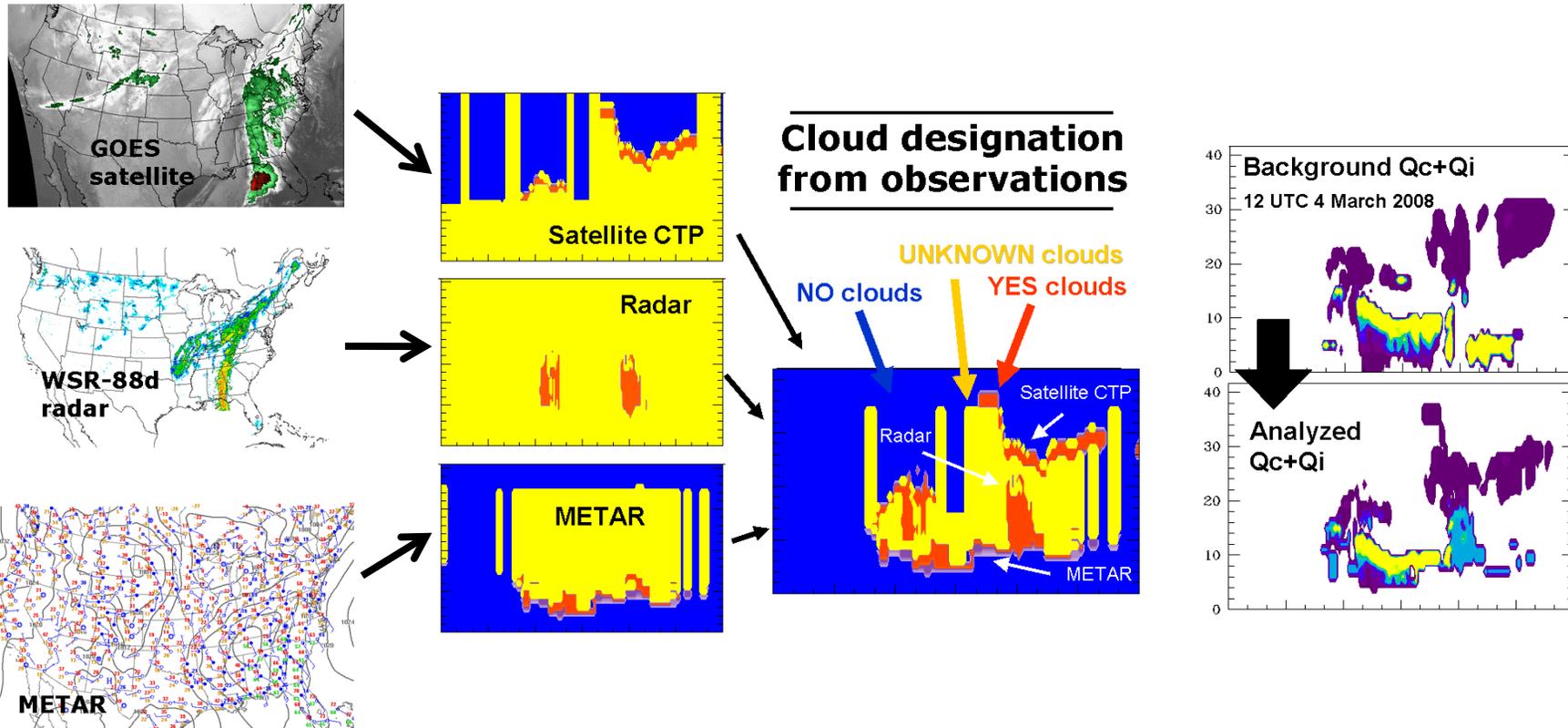


**Pixel**



# Cloud analysis schematic

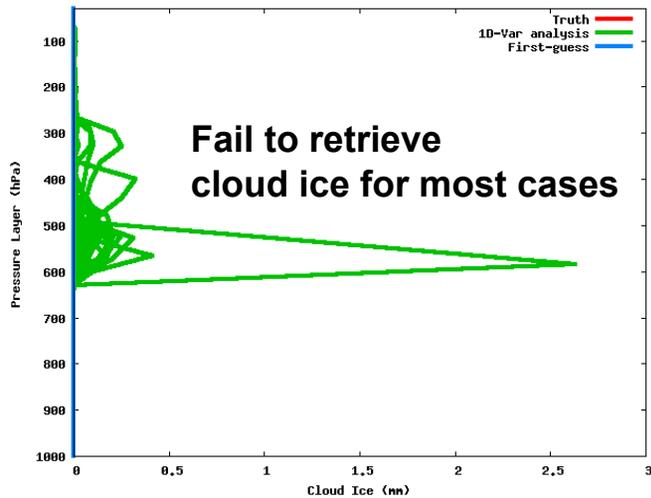
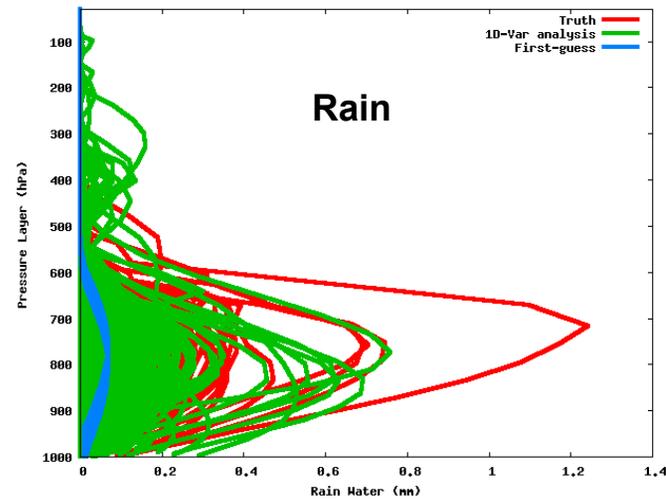
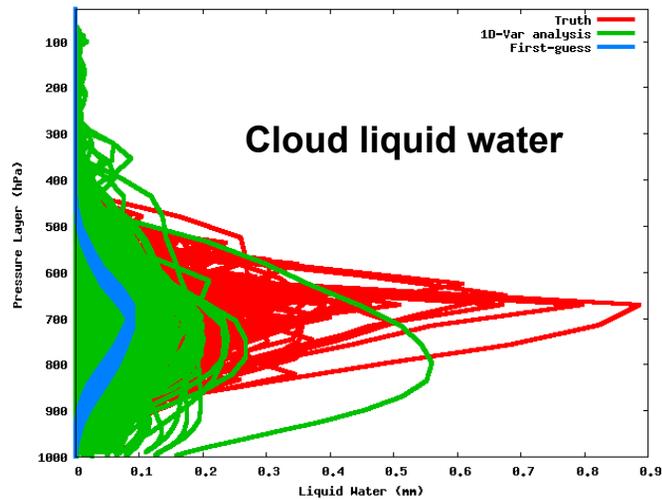
Courtesy Ming Hu (NOAA/ESRL)



observation

- Uses METAR, satellite, radar, lightning data
- Updates RR 1h-fcst RR hydrometeor, water vapor fields
- Generates latent heating from radar and lightning data

# Simulated SSMI/S radiances: 1DVar



## 1DVar Retrieval of Hydrometeors

1. Control variables: T, Q, Cloud liquid water, rain, cloud ice
2. Start from a mean cloud/rain profile background
3. Random noise to the simulated obs and T, Q background profiles

**Signal for cloud-ice is weaker than for cloud-water/rain**

